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**F-PRESS: A Stochastic Simulation Tool for  
Developing Fisheries Management Advice  
and Evaluating Management Strategies**

**by**

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## **Abstract**

F-PRESS is a stochastic simulation tool based on a simple algorithm designed to fit in with the ICES conceptual framework for software development. F-PRESS can be used to develop probabilistic assessment advice or to evaluate management strategies or harvest control rules (HCRs). In this paper, we describe and justify the underlying methodology on which F-PRESS is based and give full details of the modular structure of the simulation algorithm. We use the example of Irish Sea cod to demonstrate how the software can be used to develop probabilistic management advice or to evaluate and compare different HCRs.

*Keywords: ICES advice, fisheries management advice, evaluating management strategies, harvest control rules, stochastic modelling, stochastic simulation.*

## **Note on software development**

F-PRESS has been designed to be a flexible and adaptable piece of software. The open source nature of the program code means that it is easy for both developers and end users to adapt and edit the code. For this reason it should be made clear that the specific functions used and discussed in this paper refer to the latest full version of the program – currently F-PRESS Version 1.0 (as of February 2006). Later versions of the software may have different functionality, but the methodology and underlying approach will be the same as presented here.



## **1 Introduction**

The ICES Study Group on Management Strategies (SGMAS; ICES, 2005) identified a need for a simple and flexible simulation tool for evaluating management strategies that follows the ICES simulation framework given by the ICES Methods Working Group (WGMG; ICES, 2004a). We have designed the simulation tool, F-PRESS (Fisheries PROjection and Evaluation by Stochastic Simulation) to be used to both develop probabilistic based assessment advice and to evaluate and compare different management strategies and harvest control rules (HCRs). F-PRESS is programmed and runs using the R language and environment (R Development Core Team, 2003). The program uses open source code so that it is easy to validate and easy for an end user to adapt the code for their own uses. We have deliberately designed the underlying algorithm to be as simple as possible and aim to replicate the qualitative highly variable behaviour observed in real-world fishery dynamics using simple stochastic processes.

In this paper we discuss and justify the methodology behind our approach in designing F-PRESS Version 1.0 and give full details of the modular structure of the algorithm and how this fits into the ICES conceptual framework for software development (ICES, 2004a; 2005). We do not attempt to directly compare and contrast the approach taken in F-PRESS to existing software used by the ICES community, although descriptive comparisons are available in ICES (2005). We stress that further ongoing validation and comparison to existing software is required as the software is developed and used in different cases.

Details of how to set up the software files and run the program are given in the 'F-PRESS User Manual', while details of the code and suggestions on editing and adapting the program are given in the 'F-PRESS Technical Manual'. All the source code files that are needed to run the program, along with the manuals and example template options files and data are available from the authors.

## **2 Methodology**

### **2.1 The role of stochasticity and uncertainty in fisheries assessment and management**

Traditional assessments in the ICES community have relied on deterministic models both to evaluate the historical development of the stock and to project future states. This approach has limitations, which are highlighted when clients ask for long-term advice or the evaluation of a particular management strategy. The approach to medium term projections has been to incorporate an element of stochasticity based on the estimated variance of parameters from the most recent assessment. This approach too often overlooks bias in the most recent evaluation on the current state of the stock, and can lead to misleading interpretations of future states under assumed conditions.

To take the underlying uncertainty of the system into account requires a model that replicates the qualitative highly variable and unpredictable behaviour of the real world (including the development of the population, the performance of the assessment, and the implementation of the control measure). The approach we present here

uses a very simple model that accounts for the uncertainty in the system by adding in 'stochastic noise' so that stock and fishery parameters are randomised and vary from year to year. Furthermore, stochastic models are used to account for the high variability in recruitment and possible errors and bias in the observation / assessment process. Results are then interpreted as qualitative 'general trends', and probabilities (risk levels) of certain scenarios occurring (e.g. spawning stock biomass [SSB] falling below a reference point such as  $B_{pa}$ ) can then be calculated. These 'risk levels' and probabilities could then be used by managers to determine optimal strategies.

We deliberately avoid a highly complex simulation model that tries to explicitly include every single process that may occur in the fishery / assessment / management system (we refer to this approach as the 'absolutist' approach). Instead, we argue that as the usual ultimate aim is to find the best robust management strategy for a particular stock, the effort should be spent on testing and evaluating possible management rules / plans using a qualitatively realistic model of the real world. The key point here is that we believe a qualitatively realistic model does not have to be a 'perfect' replication of every process that happens in the real world – as long as the key features of the real system are included then the model is likely to be reasonable. An example of this is our observation / assessment model – our initial model simply assumes that observations of the virtual stock (e.g. spawning stock biomass [SSB] or fishing mortality [F]) have a level of error (added as random noise) together with a possible bias (e.g. systematic overestimate). More complex simulation tools may try and model the whole assessment process explicitly (using standard ICES assessment software) so that 'real' errors are explicit in the virtual fishery system (a process known as assessment feedback). Similarly, a complex model for recruitment may attempt to include temperature, salinity or other effects, but then these separate processes also need to be explicitly included in the simulation – which may be difficult or impossible (it is likely to be as hard to predict future sea temperatures as it is recruitment). A simple recruitment model with added random noise to account for the observed variability will have the same qualitative effect on our virtual system as the complex model (where correlation effects are not significant) but will be much easier to implement and understand.

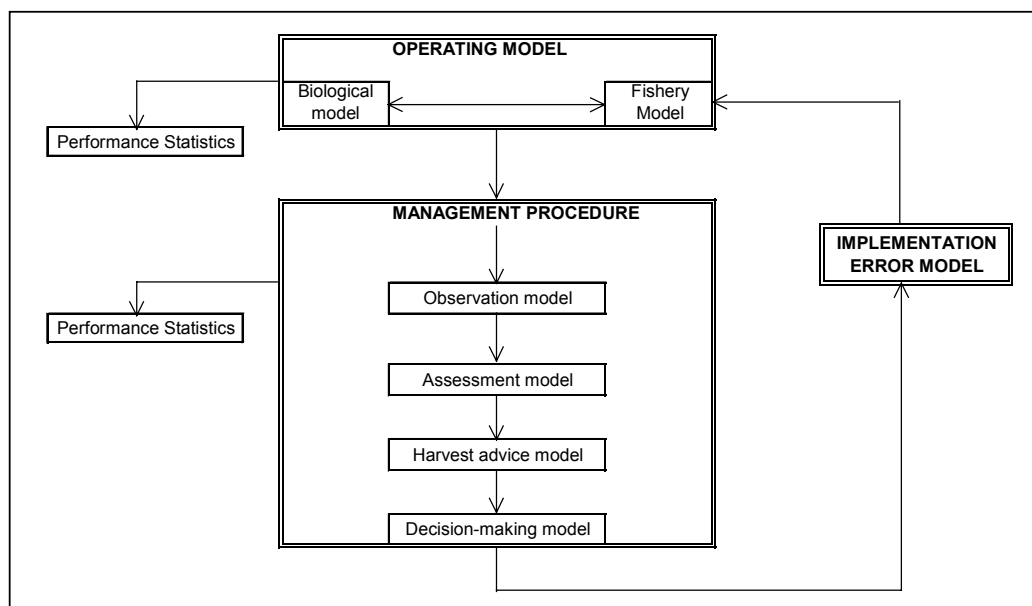
Our key point is that if a particular management strategy is robust enough to be a success in our simple but 'qualitatively realistic' model of the real world, then (unless we have failed to include a key feature of the system) it is likely that the same management strategy will also be a success in a highly complex model of the real world (and ultimately in the real world itself) so that added complexity in the model is not likely to be necessary. Limitations of this approach are further discussed in Section 3.5

## **2.2 ICES simulation framework for evaluating management strategies**

WGMG (ICES, 2004a) identified the evaluation framework approach based on simulation as the appropriate method to use to evaluate management strategies. Simulation tools can be used to conduct experiments that evaluate the response of the fishery system to the management strategy. The evaluation framework includes mathematical representations of both the true and the observed systems (data collected, assessment model used and reference points used to guide HCRs and their implementation) and so attempts to investigate the robustness of management strategies to both the intrinsic properties of the natural system and to our ability to understand, monitor and control them. Figure 1 shows a representation of the conceptual evaluation



framework recommended by WGMG (ICES, 2004a) and SGMAS (ICES, 2005). The framework comprises everything that is needed for conducting simulations to evaluate management procedures.



**Figure 1. Conceptual framework for the evaluation of management procedures, recovery plans and harvest control rules. Figure taken from ICES (2004a; 2005).**

This modular conceptual framework is also ideal for developing management advice based on the likely dynamics of the stock due to biology and fishing (where the ‘management procedure’ modules may not be used in the program). Such management advice may take the form of medium term projections of the stock under fixed catch or fishing mortality and advice can be given in terms of risk (probability of being above or below key reference points such as  $B_{pa}$ ).

In practice, most medium or long-term management strategies are likely to be case-specific and use more than (for example) a simple decision rule based on the assessment estimated stock size. In fact, there are likely to be a whole range of possible management strategies or HCRs and no single generic simulation tool will ever be able to evaluate all of them. For this reason, SGMAS (ICES, 2005) specified that any simulation tool to be used for evaluating management strategies should be designed to be as clear and simple as possible using open source coding based on the modular conceptual framework given in Figure 1. In this way, any end user (with only basic programming skills) should be able to modify the code to deal with a case-specific HCR or strategy. This approach is clearly different to the historical approach of developing ICES community software where the end user is not expected to edit the program code and software is distributed as compiled code. F-PRESS has been designed to fit in with the conceptual framework given in Figure 1. Full details of the separate modules in the simulation algorithm are given in Section 3

### **2.3 Software platform – the R language**

F-PRESS has been programmed and runs in the R software language and environment (R Development Core Team, 2003). F-PRESS is loaded as source code into the R environment and is not standalone software. All R software and packages are freely available from the R project website: <http://www.r-project.org/> and it is necessary to download the R platform in order to run F-PRESS. The simulation has been programmed using R 2.0 – the code should run in later versions of R but may not be backwards compatible with earlier versions. R has been designed as an open source programming language for statistical applications. R is a ‘low level language’ in the sense that the majority of mathematical and statistical functions have already been programmed into it (in contrast to ‘high level languages’ such as C or Fortran). This allows the programmer to quickly and easily produce things like random numbers from distributions. The only disadvantage with R comes from the fact that the source code is not compiled – this means that simulations are likely to run slower than if they were programmed in a ‘high-level’ language and then compiled. This is not likely to be a major problem however as (in our experience), most programmers spend their time writing and debugging code rather than actually running the final simulations (meaning using R may even save time in the long term). The fact that programs do not need to be compiled to run in R means that all code is always transparent ‘open source’ and can easily be interpreted by other programmers.

Because of this transparency and the functional structure of R, various working groups such as WGMG (ICES, 2004a) and SGMAS (ICES, 2005) have put forward suggestions to use R as a common language. Code written in R will be open and easy to understand and interpret for other fisheries scientists. The code writer will find it much simpler to use the inbuilt functions of R in their code rather than ‘starting from scratch’ in a high level language. If F-PRESS were to be used by more than a few users, then the development of the code should be handled by procedures designed for the development of open source code software, such as Concurrent Versions System. Technical details for this as well as the philosophy behind ‘Opensource’ software is given in ICES (2004a).

For further details on the R language see the manuals ‘An Introduction to R’, ‘R Reference Manual’ and ‘R Language Manual’ available from the Help window in the R environment or online at <http://www.r-project.org/>.

## **3 Simulation algorithm**

A summary of the key points relating to the algorithms of F-PRESS and considerations for its implementation are given in Appendix I. The following subsections describe the simulation tool in more detail.

### **3.1 Operating model**

ICES (2004a; 2005) defines the operating model as ‘A virtual world that is a simplified representation of reality. It’s main components are fish and fisheries.’ The operating model should consist of a fishery model that considers direct interactions between the fishery and fish stock(s) (exploitation), and a biological model that repre-

sents the underlying natural dynamics of the fish stock(s) (e.g. natural mortality, recruitment).

The operating model of F-PRESS uses the standard single-species age-structured population with exponential mortality model used in most virtual population analyses (e.g. Baranov, 1918; Beverton & Holt, 1957):

$$N_{a+1,t+1} = N_{a,t} \exp(-F_{a,t} - M_{a,t}), \quad (1)$$

where  $N_{a,t}$  is the population numbers at age  $a$  in year  $t$ , while  $F_{a,t}$  and  $M_{a,t}$  are the fishing and natural mortalities respectively that the cohort are subject to. The operating model does not include any spatial elements or allow for mixed species interactions.

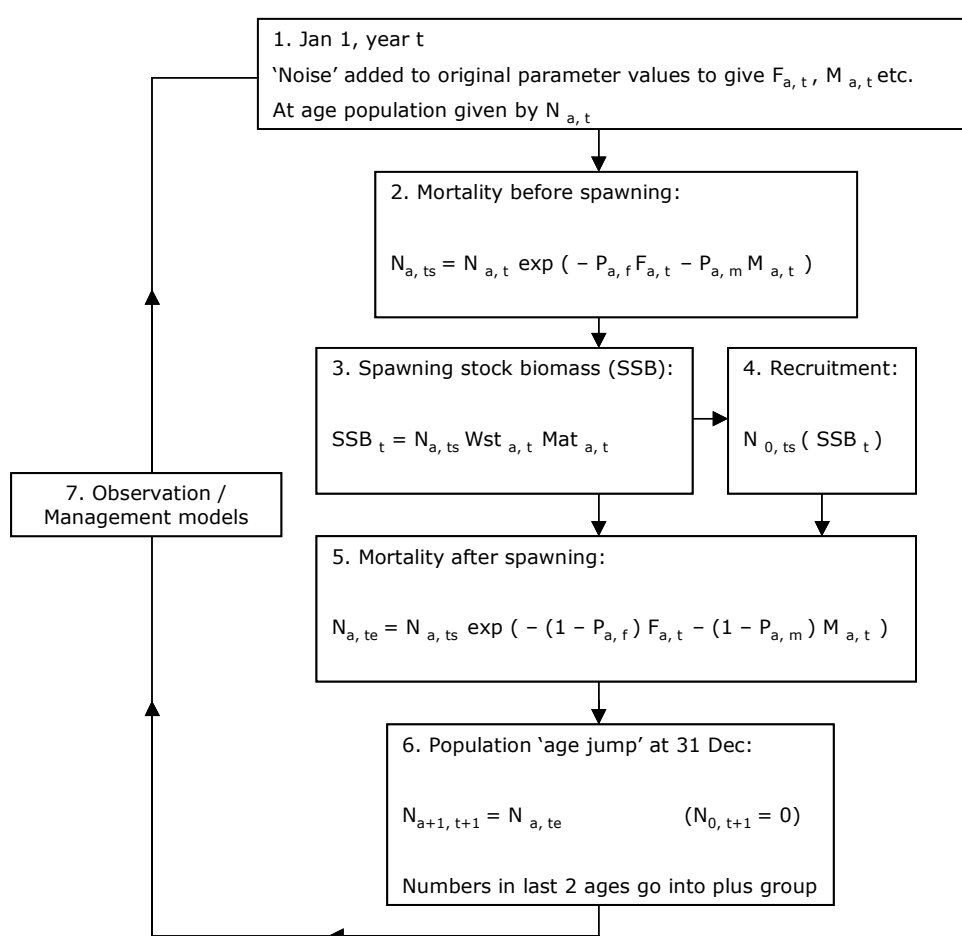


Figure 2. Flow diagram illustrating the algorithm (and equations) used in the F-PRESS 'operating model'. Recruitment, observation/assessment and management are all modelled separately as described in the relevant sections. In this diagram, fishing mortality,  $F$ , is the sum of separate landings and discard mortalities. Notation:  $N_{a,ts}$  = population numbers at age  $a$  at spawning time in year  $t$ ;  $N_{a,te}$  = population numbers at age  $a$  at end of year  $t$ ;  $P_{a,f}$  = proportion of fishing mortality at age  $a$  before spawning;  $P_{a,m}$  = proportion of natural mortality at age  $a$  before spawning.

Figure 2 shows a detailed diagram of the algorithm used as the operating model in F-PRESS. The population characteristics are randomly generated at the start of the year (see below); the population then suffers mortality, undergoes spawning (recruits are generated using a simple recruitment function) and then suffers mortality for the remainder of the year. At the end of the year the population all moves up an age class, with new recruits entering the relevant age class (depending on the stock recruitment age). The final two age categories are combined as a plus-group.

It should be noted that the basic operating model algorithm given in Figure 2 is fairly standard across most fishery models used by ICES. What is novel about our approach is how stochasticity is introduced (see below), and how the results are interpreted (see Section 4).

The key point in our operating model is that we model the initial population numbers (first year only) and the characteristics of the population (weight at age, maturity at age, natural mortality at age) and of the fishery (fishing mortality at age) as stochastic variables. In general, each parameter (stock or fishery characteristic) has a mean value and CV (coefficient of variation) value. The CV data can come from assessment data (if available) or can be assigned by the end user (e.g. assume a 20% CV). It should be stressed that, as our ultimate aim is to test the robustness of various management strategies to realistic levels of uncertainty in the system, these CV values do not have to be exact values drawn from assessments (so that progress can be made if this CV data is unavailable). If the end user arbitrarily assigns CV values then results should only be considered in relation to the assumptions made as part of this assignment. It is also worth considering that using only observed CV values in the simulation could lead to the simulated random noise being constrained by the observation program rather than reflecting true underlying variability, so care should be taken. Noise is added to the relevant parameter values by drawing from a Normal distribution with the appropriate mean and CV values relevant to the particular parameter that is being randomised. (The assumption of Normally distributed noise can be changed and any distribution could be used. This would require a simple change in the source code by the end user). For example, assume our weight at age 1 is  $x$  (kgs) with an associated CV of  $y$ . In our simulation run, we draw a new value for weight at age 1 from a Normal distribution with mean  $x$  and variance  $(x*y)^2$ , i.e.  $N(x, (xy)^2)$ . Note that with this model, there is a low (but non-zero) probability of drawing negative numbers: any negative numbers drawn are rejected and a new draw is made (so the distribution used in this example is more correctly a 'truncated Normal distribution'). This process is repeated for each at age parameter. The initial population numbers are treated as stochastic in the first year of the projection only, but all other parameters are calculated as described above (using the original values as mean and CV) at the start of each year. By adding noise to the original parameter values each year, our stock and fishery characteristics will on average not change over time. If required, it would be possible to alter the code to allow for noise to be added to the randomised parameter value from the previous year (rather than the original input parameter value), which would lead to a 'random walk' in parameter space. Furthermore, to keep the model as simple as possible, we do not model any temporal correlations in the stock, see Section 3.5.

### **3.1.1 Recruitment models**

The two largest factors in the year-to-year fluctuations in size of most fish stocks are fishing and recruitment. Looking at any historical recruitment data set, it is

clear that there is usually extremely high variability in year-on-year recruitment values. This high variability should be replicated in the operating model of the simulation – a model that just assumes a fixed average level of recruitment every year is unrealistic and would not reproduce the qualitative behaviour observed in the real world.

Some quite complex recruitment models have been suggested in the literature (see review in Needle, 2002) where recruitment is dependent on not only SSB but also temperature, salinity etc. Such models require these separate processes to be explicitly included in the simulation, which is likely to be highly data intensive (a problem with the ‘absolutist’ approach). However, as discussed in our methodology, we believe that (in most cases) a simple recruitment model with added random noise to account for the observed variability will have the same qualitative effect on our virtual system as the complex model but will be much easier to implement and understand.

We have included various recruitment models in the simulation tool and full details are given in the ‘F-PRESS User Manual’. When making a simulation run, the end user can specify which recruitment model to use, or (with the modular structure of the operating model, see Figure 2), it is extremely simple to add a new recruitment model (by editing the source code). In general, the recruitment models are either based on historical data (bootstrapping data values, or deterministic function fit) or are given by user input parameters (e.g. a fixed mean value, or a linear relation with SSB). These functions or values may then be dependent on the current SSB level of the virtual population to give an expected recruitment value (e.g. Ricker). For those recruitment models based on a deterministic function or point-value, variability is added in a similar way to the fishery characteristics as described in Section 3.1. The deterministic value of recruitment is taken as the mean value of a Normal distribution with a given CV (specified by user or calculated from historical data), and a new value for recruitment is randomly drawn from this Normal distribution (rejecting negative draws). Other distributions could be used if desired by the end user but this would require some (basic) editing of the code. Obviously, if a CV value of zero is specified then the recruitment model will be completely deterministic but this may not produce qualitatively realistic behaviour. An example of a typical stochastic recruitment model used in the simulation is given below:

#### **Example – ‘Stochastic Ricker’ function**

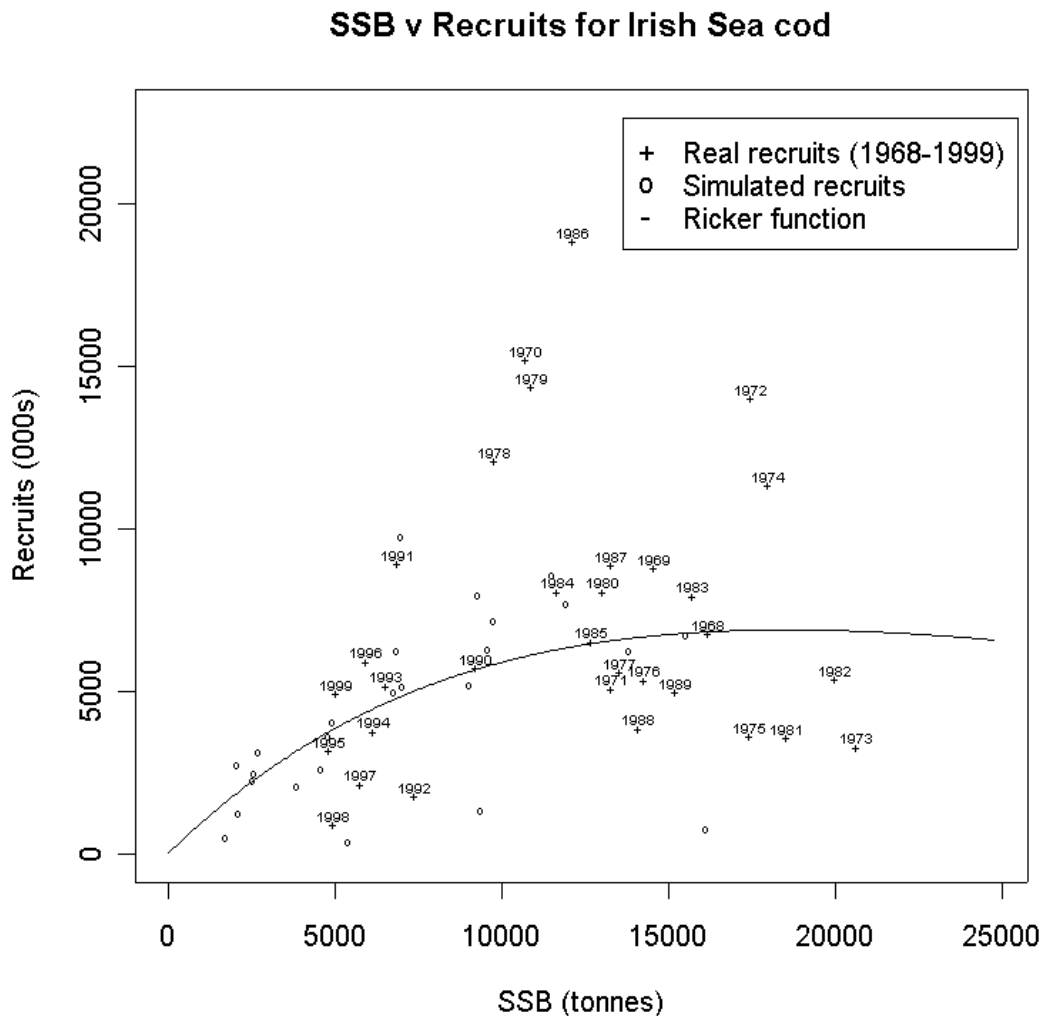
The standard Ricker stock and recruit function (Ricker, 1954) takes the form

$$R = \alpha S \exp(-\beta S), \quad (2)$$

where  $S$  is the spawning stock biomass (SSB),  $\alpha$  and  $\beta$  are parameters estimated by fitting the function to historical data, and  $R$  is the expected number of recruits. The function is based on the biological assumptions that at zero SSB, recruits will be zero, and at very high SSB levels, recruitment will be reduced due to density dependent effects (e.g. cannibalism). The function is completely deterministic since, given the same value of SSB and assuming  $\alpha$  and  $\beta$  are fixed, it will always produce the same expected value for  $R$ . This deterministic function is not altogether realistic, especially when considering the large amount of variability observed in recruitment (Figure 3).

A more realistic model for recruitment should include natural variability in a quantifiable way. In simulations using a stochastic version of this model, we randomly draw our recruit values from a normal distribution with mean  $R$  and standard deviation

$R \cdot CV$ , i.e.  $N(R, R \cdot CV)$ , where  $R$  is given by (2), and  $CV$  is the coefficient of variation in the historical recruitment values (for simplicity we use this estimate for the  $CV$  value; it is also possible, if more complex, to use a  $CV$  value calculated from the transformed residuals from the Ricker function fit to the historical data). For Irish Sea cod 1968 – 1999, the  $CV$  in the recruitment values is approximately 0.6 (data from ICES, 2004b) and typical values for recruitment given by this method are shown in Figure 3 along with the historical data set.



**Figure 3. Plot of numbers of recruits against spawning stock biomass (SSB) for Irish Sea cod between 1968 and 1999 (XSA data from ICES, 2004b). Assessment data is compared to simulated values that have been generated using a ‘stochastic Ricker function’. Due to its stochastic nature, the simulated data shows qualitatively similar behaviour to the assessment data. The deterministic Ricker function that has been fitted to the real data is clearly only a weak approximation, as it does not allow for the typically large amounts of variability observed.**

In this example, where the dependency between recruitment and environmental conditions is simply modelled as random noise added to a fixed function, stationary environmental conditions are assumed. While it is not necessary to understand

the mechanism that relates temperature (for example) to recruitment, the assumption we make is that there is no change or trend in the environmental variable over time.

### **3.1.2 Fishery model**

When running a projection with F-PRESS, the end user has the option of specifying whether the fishery is regulated using fishing mortality,  $F$  (or a range of  $F$  values), or a TAC (or a range of TACs). The underlying code actually always calculates mortality using  $F$ , but if the TAC option is chosen it uses a simple iterative routine to find an  $F$  multiplier that gives the required TAC.

The input data (see Section 3.4.1) requires the user to specify an  $F$  at age vector for the initial year (and a discard  $F$  at age vector may also be specified but is not required). As described in Section 3.1, this  $F$  vector (and discard  $F$  vector) has noise added to it at the beginning of each year so that the selection pattern will vary slightly from year to year (the amount of variation depending on the input CV values).

If the user specifies a required value of  $F$  or TAC in any particular year then the simulation calculates an  $F$  multiplier that when applied to the (newly randomised)  $F$  vector will produce the required  $F$  or TAC. For example, if the starting  $F$  at age vector has  $F = 0.5$  (calculated over the relevant age classes) and the user requires  $F = 0.75$ , then an  $F$  multiplier of 1.5 is applied to the starting  $F$  at age vector. The same  $F$  multiplier is also applied to the discard  $F$  at age vector. An iterative routine is used to find an  $F$  multiplier that gives the required TAC and this is then applied to the  $F$  and discard  $F$  at age vectors in a similar way.

It should be noted that there are some limitations to this simple approach. In particular, it may not be the case that the same multiplier should be applied to all the age classes in the  $F$  or discard  $F$  at age vector. For example, if a low TAC is introduced then we may expect higher levels of discarding. Currently, our simulation will not deal with this problem. It would be straightforward to introduce an  $F$  multiplier at age vector (rather than a single  $F$  multiplier), and it would also be possible to use a relation between the  $F$  multiplier applied to the  $F$  vector and the  $F$  multiplier applied to the discard  $F$  vector (e.g. in some cases one may expect an inverse relation between these). End users with basic programming skills could make these changes if required.

Implementation errors are included in the operating model of F-PRESS (rather than as a separate module as shown in the conceptual framework in Figure 1). If the projection uses  $F$ , then random noise (CV) and a bias factor ( $b$ ) can be included to account for both operational uncertainty (small random fluctuations in  $F$  or catch from year to year) and systematic over-exploitation respectively. A new (non-negative)  $F$  value is randomly chosen from a Normal distribution  $N(F*b, (F*b*CV)^2)$ . Obviously, if  $b=1$  and  $CV=0$ , then the  $F$  value used in the virtual fishery is the original deterministic input value and there is no implementation bias or noise. In this way, the value of  $F$  to be used by the fishery is randomised (as are the relative  $F$  at age selectivity values as described previously). The simulation then calculates an  $F$  multiplier to apply to the randomised  $F$  at age vector so that the new randomised (and possibly biased)  $F$  value is produced by the virtual fishery. If the projection uses TAC, then a similar bias factor can be applied to the TAC value that is used and this new value can also be randomised in a similar way to account for operational uncertainty in the fishery. In this case, a new (non-negative) TAC value is randomly chosen from a Normal distribution

$N(TAC*b, (TAC*b*CV)^2)$ . The simulation then calculates an F multiplier to apply to the randomised F at age vector so that the randomised (and possibly biased) TAC value is produced by the virtual fishery.

### **3.2 Observation and assessment model**

The operating model can be used on its own to make simple hindcasts (a projection brought forward from a date in the past, e.g. 1999-2003) or forecasts (a projection forward into the future, e.g. 2005-2010) of the stock (see Section 4.1). In this case we have 'perfect' knowledge of our virtual stock as we can see the exact stock status in the output data from the simulation run.

However, if we wish to simulate the effect of a particular management strategy then we need to account for the observation and assessment processes where errors in the perceived stock status are likely to be introduced. Unlike a virtual population, in the real world we will never know the full details about a stock. In reality, a management regime is likely to be based on these observed stock states (with their inherent errors), so it is essential that they are included in the simulation.

As discussed in the methodology, there are two ways of dealing with this. Complex simulation tools may try and model the whole assessment process explicitly (using standard ICES assessment software) so that 'real' errors are explicit in the virtual fishery system (assessment feedback). In contrast, the model we use simply assumes that observations of the virtual stock relevant to the management strategy (e.g. SSB or F) have a level of error (added as random noise) together with a possible bias (e.g. systematic overestimate or underestimate). It should be pointed out however, that the maximum possible level of complexity of any observation / assessment model will be limited by the level of complexity of the operating model (e.g. the assessment model can't include discarding if the operating model does not also include it).

At the most basic level, our simple approach and the complex approach will both produce the same end result – an error in the estimation of the stock size (or F for example), and it is this qualitative behaviour we aim to replicate. Our approach is not likely to give the exact results that would occur in the real world but we would suggest that it is unlikely that a highly complex model would do this either.

In the current version of our simulation tool we use HCRs based on the observed levels of F and/or SSB. For this reason our observation/assessment model introduces noise and bias to these parameters only. It would be simple to adapt our current model to include observational errors on any of the virtual stock characteristics. A specified delay is included in the model to account for the fact that assessments are usually carried out using data from the previous year(s). Bias (to account for systematic under/over estimation) and noise (to account for errors) is introduced to F and/or SSB in exactly the same way as described in Section 3.1.2. New values are drawn randomly from (in the case of F) a Normal distribution  $N(F*b_a, (F* b_a *CV)^2)$  and similarly for SSB (note that the bias  $[b_a]$  and CV parameters take different values to those described in earlier sections).

As the simulation is designed in a modular framework (Figure 1), an end user may easily add or adapt much more complex observation and assessment models. A further advantage of our approach is that the end user can specify the exact level of



bias or random error in the observation/assessment process. This allows one to clearly see how robust a particular management strategy or HCR is to levels of error. With the more complex assessment feedback approach it becomes much harder for the end user to quantify and understand the effect of error propagation.

### 3.3 Management and decision making model

SGMAS (ICES, 2005) give the following description for the 'management model' component of the conceptual framework given in Figure 1:

*'This component uses the assessment results to compare the perceived status of the stock and fishery against a pre-determined set of benchmarks in order to formulate advice. On many occasions, a harvest control rule will be used (a recovery plan is regarded as being a special case of a harvest control rule). These rules represent pre-agreed actions taken conditionally on quantitative comparisons between indicators of the status of the stock and some sustainability or optimality indicators.'*

The 'decision making model' is simply a component that may alter the result given by the management model. This could be necessary if considering mixed-species fisheries or to take into account political decisions. The current version of F-PRESS assumes that the result of the management model is unchanged by any further decision-making (it would be simple to edit the code to allow this to change).

SGMAS (ICES, 2005) make the point that it is unlikely that any single simulation tool will be able to run and evaluate all possible management strategies – there are simply too many possibilities. Instead, it was suggested that a simulation tool should be designed so that it is as easy as possible for the end user to edit the code and add a particular management routine or HCR. F-PRESS is ideal for this purpose as the underlying model is deliberately simple and the program code is open source and freely available. The 'F-PRESS Technical Manual' describes the program code in more detail and gives suggestions on how to edit or adapt the code.

Nevertheless, there are several 'generic' HCR routines included with the F-PRESS simulation package that are described in more detail in the 'F-PRESS User Manual'. In general, the primary variables in the supplied HCRs are the parameters  $F$  and  $SSB$  that come from the observation/assessment model. There are also further fixed parameters that can be specified such as threshold points where the decision rule in the HCR acts (these could be  $B_{lim}$  and  $B_{pa}$  for example). The user may also specify limits in the year-on-year percentage change in TAC or  $F$ . It is also possible to set a time period for management actions so that changes brought about by the HCR only act every second or third year for example. Most decision rules are simple algorithms based on logical statements as shown in the example below. More complex examples could of course be designed where the decision rule is based on more than just a simple logical statement using the specified variables and parameters. An example of a 'typical' generic HCR is given below:

#### **Example – HCR with fixed TAC and reductions relative to $B_{pa}$**

In this example the decision rule is as follows:

1. If ( $SSB > B_{pa}$ ) then TAC = 10,000 tonnes;

2. If  $(SSB < B_{pa})$  then  $TAC = 10,000 * SSB / B_{pa}$  tonnes;

This decision rule simply states that if the observed SSB is below the reference point  $B_{pa}$ , then the specified annual TAC (10,000 tonnes) is reduced by the same factor that the observed SSB is below  $B_{pa}$  ( $SSB / B_{pa}$ ) and this new TAC is then used for the following year. If the observed SSB is not below  $B_{pa}$ , then the original specified annual TAC (10,000 tonnes) is used for the following year. Note that the decision rule uses the observed SSB that comes from the assessment/observation model so that observation errors can affect the HCR outcome. The above example assumes TAC cannot increase above 10,000 tonnes for the whole projection period, but a further addition to the rule could be to increase the TAC if  $SSB > B_{pa}$  using the inverse of rule 2.

### **3.4 Implementation and output of simulations**

#### **3.4.1 Input data requirements**

F-PRESS requires three separate data input files – population and fishery at age data, recruit history and catch history. The latter two files are only needed if the user requires them – for example the recruit history file is needed if a recruitment function that uses historical data is chosen, while the catch history file is needed if a hind-cast is being completed and the user wishes to replicate historical F or catch values that vary each year. Full details of what is required in these data files (and instructions on how to set up the files) are given in the 'F-PRESS User Manual', but the main points are summarised below:

##### **At age data file**

This file contains the data that F-PRESS uses to generate the randomised at age values used in each year of the projection (see Section 3.1). The file consists of a data array of 18 columns with a number of rows equal to the number of required age classes. The at age data in each column is as follows:

1. Age (the last age class is always a plus group);
2. Initial population numbers (in thousands);
3. CV of initial population numbers;
4. Spawning weight (in kg);
5. CV of spawning weight;
6. Catch weight (in kg); (\*)
7. CV of catch weight;
8. Maturity ogive (proportion mature, value between 0 and 1);
9. CV of maturity;
10. Fishing mortality;
11. CV of fishing mortality;

12. Proportion of fishing mortality before spawning; (\*\*)
13. Discard fishing mortality; (\*\*\*)
14. CV of discard fishing mortality;
15. Natural mortality;
16. CV of natural mortality;
17. Proportion of natural mortality before spawning;
18. Column filled with zeros (used by program to function).

Notes:

(\*) spawning weight and catch weight can be the same;

(\*\*) proportion of fishing mortality before spawning applies to both fishing and discard mortality;

(\*\*\*) discard mortality can be set to zero if no data is available.

Most of the required data should be available as part of a typical ICES stock assessment (e.g. XSA data input). If the CV values are all zero then the projection can be deterministic (if the recruitment function is also deterministic). The CV values can be taken from assessment data or estimated (e.g. by assuming a 20% CV on all parameters). This allows progress to be made in an assessment if the data is uncertain.

### **Recruitment history data file**

The recruitment history data file consists of three columns:

1. Year;
2. Recruitment (thousands);
3. SSB (tonnes).

The historical recruitment data can be used to produce recruitment functions (e.g. Ricker) or for bootstrapping. Alternatively, if recruitment values are input for years after the start year of the projection then the user can choose for these values to be used instead of the specified recruitment function. An example of when this would be useful is if doing a hindcast projection where the user wishes to replicate a historical low recruitment and then carry on the projection into the future using a stochastic recruitment function.

### **Catch history data file**

The catch history data file consists of three columns:

1. Year;
2. Catch (tonnes);
3. F.

The historical catch data can be used to replicate historical catches or F values in a hindcast projection. Note that, if catch or F values are specified for years ahead of the start year of the projection, then the user can choose for these values to be used instead of the TAC or F values the projection would otherwise have used. This is not only useful for doing hindcasts – it also allows the user to specify the TAC or F for all the future years of the projection (if this is required).

### **3.4.2 Running the simulation**

No programming experience is required by the end-user to run projections to be used in management advice or to run evaluations of very simple generic HCRs (see Section 4). Evaluations of more complex HCRs would require some basic programming skill to alter the code but F-PRESS has been designed to make this as simple as possible to do. Full details of how to run the simulation and how to edit and adapt the code are given in the 'F-PRESS User Manual' and the 'F-PRESS Technical Manual' respectively. The actual procedure of running an F-PRESS projection is very simple. Assuming the data files are set up correctly (see Section 3.4.1), the user just has to fill in an 'Options' file with the required simulation parameters and then load this 'Options' file into the R environment. The program will run and automatically produce the most relevant graphical output (further graphical output can be produced, see Section 3.4.3).

It is also important to consider how the user should set up F-PRESS and how results of projections and evaluations of HCRs should be interpreted. Clearly, a stochastic simulation such as F-PRESS will produce different results each time it is run so that the results of a single run do not have much meaning except as illustrations of 'typical' behaviour. Instead, it is useful to run a number of iterations (usually no more than 1000 iterations are required). It is then possible to look at the average behaviour of the stock and general trends, or to calculate probabilities associated with the risk of the stock being at certain levels.

There are two main ways of running F-PRESS:

Simulation option 1: A projection is completed for a number of years with a fixed F or TAC each year. The user can specify 'historical' F or catches and can also use a HCR. The projection is completed for a number of stochastic iterations and results are collected over all the iterations.

Simulation option 2: A range of F or TAC values are specified by the user and the simulation completes a whole iterative run of projections (as described in 1 above) for each value of F or TAC. Results can then be compared.

Clearly, running option 2 will take longer than simply running option 1, but will provide much more information. If no HCR is specified, then these simulation options can be used to give an idea of the current state of the stock (e.g. by making a hindcast forward from the year when the assessment data is 'converged' to the present year) and the likely state in future years under a range of different fishing options, see Section

4.1. If a HCR is specified then the results from simulation runs can be compared for different HCRs and the relative merits of each HCR can be seen, see Section 4.2. In this case useful performance statistics (ICES, 2005) could be: mean yield over the years in the projection, variability in yield, stock size in final year of projection, probability of stock falling below  $B_{pa}$  (or  $B_{lim}$ ) during the projection, etc.

It should be stressed that the results of any simulation run should be treated as indicative rather than the exact result that we would expect to happen in the real world. It is fair to argue that traditional deterministic 'point-value' or 'averaged' predictions usually give the 'most likely' results for the current and future state of the stock. However, it is crucial to understand that the 'most likely' result may actually have a low probability of occurring. For example, consider rolling two dice and adding the score: the 'most likely' result is a 7, but this has only a 1 in 6 chance of actually occurring. It is essential to also consider the range and variability in any simulation results and these results are better presented as probabilities of particular events occurring (e.g. probability of falling below  $B_{pa}$ ).

### **3.4.3 Data and graphical outputs**

The main graphical options available in F-PRESS are:

#### **Simulation option 1:**

- i) time-series plots of SSB, catch, F, and recruitment.

#### **Simulation option 2:**

- ii) plot of F or TAC against stock size in final year of projection;
- iii) plot of F or TAC against probability of being below (or above) stock reference points (e.g.  $B_{lim}$  or  $B_{pa}$ ) during projection;
- iv) plot of F or TAC against mean yield over projection and variability in yield over projection.

Other graphical functions are also available such as plots of recruitment e.g. Figure 3 (full details are given in the 'F-PRESS User Manual'). As the program saves all relevant data in files, it would also be possible for an end user to create their own graphical outputs if required by editing the source code. For further examples of the graphical output from F-PRESS, see Section 4.

## **3.5 Limitations of our approach**

Although we believe we have provided a good justification for the methodology of our projection simulation there are nevertheless some important limitations to our approach and the current simulation algorithm. Some of these limitations can be overcome by editing or adapting the current version of the code, while others are intrinsic to the approach we have used.

**CV data** – the stochasticity is introduced using the level of uncertainty specified by the CV values in the input data. This CV data may not be available for all parameters. It is possible to proceed by using estimates but this becomes an arbitrary choice and may leave results open to criticism.

**Recruitment** – many of the recruitment functions in the simulation allow for both SSB and recruitment values that are outside the range of historically observed data (e.g. Ricker function, see Section 3.1.1). Where this is the case any results should be treated with caution, as the recruitment functions may not be valid. (This will always be a problem with recruitment functions based on historical data and is not a problem limited to F-PRESS).

**‘Shifting baseline’ (or temporal trends)** – F-PRESS uses the original input stock and fishery parameters to produce randomised parameters each year. This means that over the whole projection the average at age weight, maturity etc would be expected to be close to the original input values. If the stock characteristics are expected to remain similar during the period of the projection then this is no problem. However, if it is expected that stock characteristics will systematically change over the period of a projection then our simulation would not be suitable. An example of this might be a 50-year long-term projection where there is expected to be a gradual change in sea temperature that affects the stock characteristics. This shifting baseline problem could be modelled in the simulation but would require the code to be adapted by the end user.

**Correlation** – noise is added randomly to all the at age stock and fishery parameters. However, in reality it may be that there are time-series correlations in the variability in these parameters. For example, if age class 1 has an above average weight in a particular year (due to random parameter generation), then age class 2 in the next year of the projection may also be expected to be above the average weight (as it is the same cohort). However, to keep the program as simple as possible, F-PRESS does not model these possible temporal correlations. Similarly, as we have used a deliberately simple observation/assessment model we are unlikely to be able to replicate the exact nature of errors and correlations that may occur using more complex assessment feedback approaches.

**Speed** – as discussed previously, R is a ‘low-level’ language meaning that program code does not need to be compiled and is easy to edit and debug. However, programs using R will run significantly slower than similar programs compiled from ‘high-level’ languages such as C or Fortran. In our experience when making a software tool from scratch, it is usually the programming, editing and debugging the code that takes most of the time (rather than the actual running of the simulation), so in the long run using R may actually save time.

**Validation** – the current version of the program code has been tested with a number of stocks under all the different simulation options. Although the program has already been informally used at ICES working groups (e.g. WGNSSDS 2005), testing has been limited to a few individuals so ongoing validation of the code is required.

**Code editing** – the source code has been designed so that end users may edit and adapt the program for their own needs. While this means the program remains as flexible as possible it also means that errors are likely to be introduced. Thus if an end user edits the source code, the results of their projections should be subject to extra scrutiny and their coding should be validated if possible. This will always be a problem with an open-source approach – the best solution is that all code should be made transparent and tested by as many users as possible before accepting any results. The development of the code should be handled by procedures designed for the development of open source code software, such as Concurrent Versions System, see ICES

(2004a). Note that in programs using compiled code (C and Fortran), if the source code is not made available then errors in coding may never be realised.

## **4 Examples of applications to management advice**

### **4.1 Risk based assessment advice**

#### **4.1.1 Estimating stock size**

F-PRESS can be used to give an estimate of the likely current stock size by hindcasting forward from an earlier year to the present year. It is usually best to start the hindcast in a year when the assessment data has 'converged' and the input data is likely to be more accurate and less liable to retrospective errors. The projection can then use the observed historical catches or if these are thought to be incorrect, a specified value of  $F$  or TAC for each year (by using the catch history file the user could specify a different value for every year of the projection if required).

The following output plots in Figures 4 – 6 have been produced using simulation option 1 (see Section 3.4.3) under various parameters (see figure captions). The input and recruitment data used is for Irish Sea cod (data from ICES, 2004b) at the start of 1999 (see Kelly et al, 2006), although it should be noted that the 'historical' catches and  $F$  used are fictional. Each projection has been completed for 100 iterations. In each figure, time-series plots of SSB, catch,  $F$ , and recruitment are shown. In each of these plots the mean value over all iterations is shown by the solid black line, while the distribution of the individual iterations is given in a box and whisker plot for each year. In the box and whisker plots, the box represents the middle 50% of the data values (25 percentile to 75 percentile); the median value is marked in the centre of the box (50 percentile), while the whiskers represent the smallest and largest data values.

#### **4.1.2 Short-term management advice**

The following output plots in Figures 7 – 9 have been produced using simulation option 2 (see Section 3.4.3). In all projections,  $F = 1.5$  (with no bias or CV) for 1999 – 2002, and then takes a fixed value (with no bias and CV = 0.1) for 2003 – 2004. Projections have been completed with different final fixed values of  $F$  ranging from 0 to 2. The input and recruitment data used is for Irish Sea cod (data from ICES (2004b) at the start of 1999 (see Kelly et al, 2006), while the 'historical'  $F$  used is fictional. Each projection has been completed for 100 iterations.

Figures 7 – 9 show the final SSB at the end of 2004, the probability of being below  $B_{lim}$  or  $B_{pa}$ , and the mean and variability of yield, all against the fixed value of  $F$  used in the final two years of the projection. The box and whisker plots in each figure show the distribution of the stochastic iterations of each projection and the percentiles displayed are the same as described in the previous section. From these plots a manager would be able to see the likely short-term effects of using different values of  $F$ . Note that similar projections and plots can be completed using a range of fixed TAC values instead.

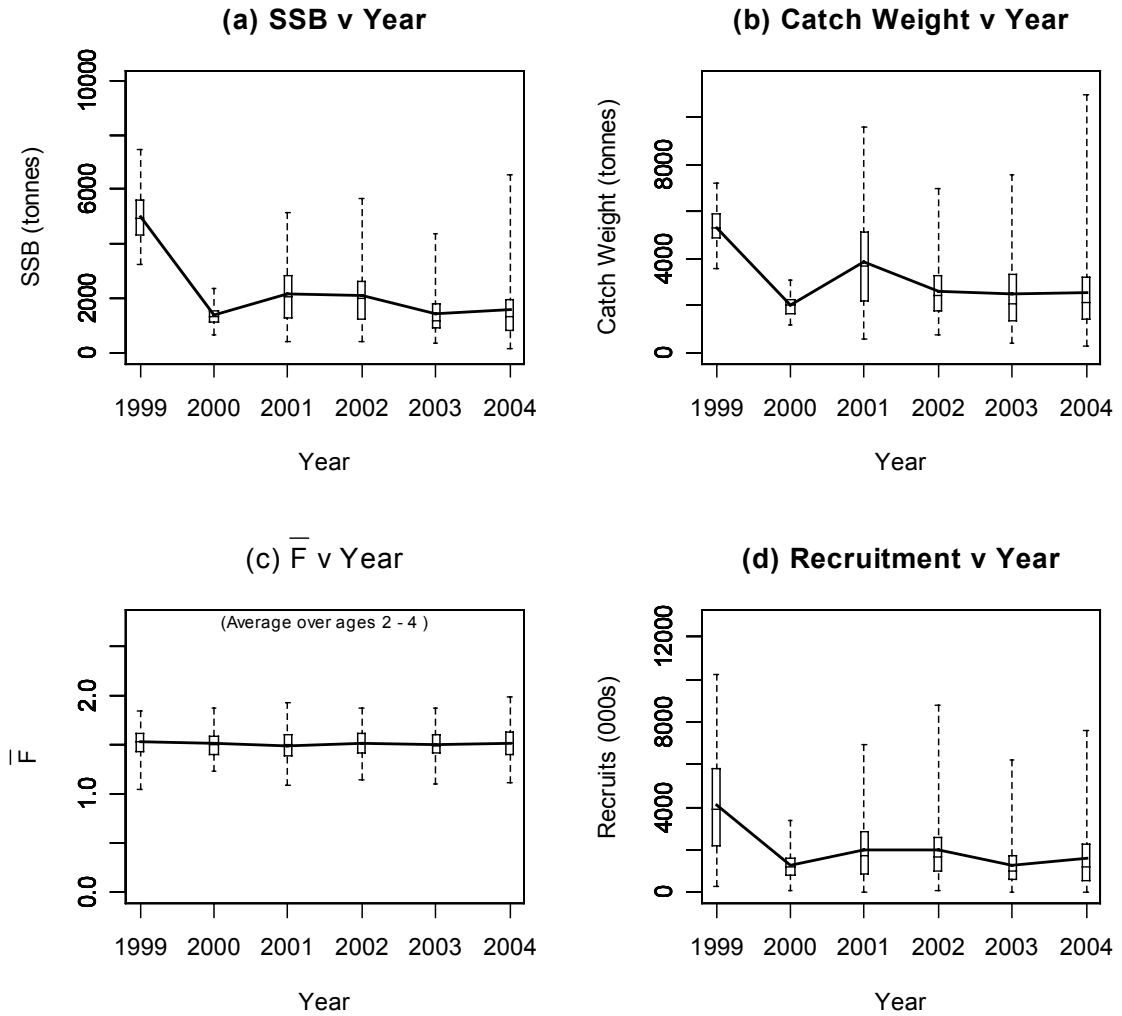


Figure 4. Time series plots of SSB, catch,  $\bar{F}$ , and recruitment, for projection of Irish Sea cod completed from 1999 – 2004. Projection uses  $\bar{F} = 1.5$  for each year of the projection, with no implementation bias and a CV on  $\bar{F}$  of 0.1. Recruitment is modelled using a stochastic Ricker function based on historical data.



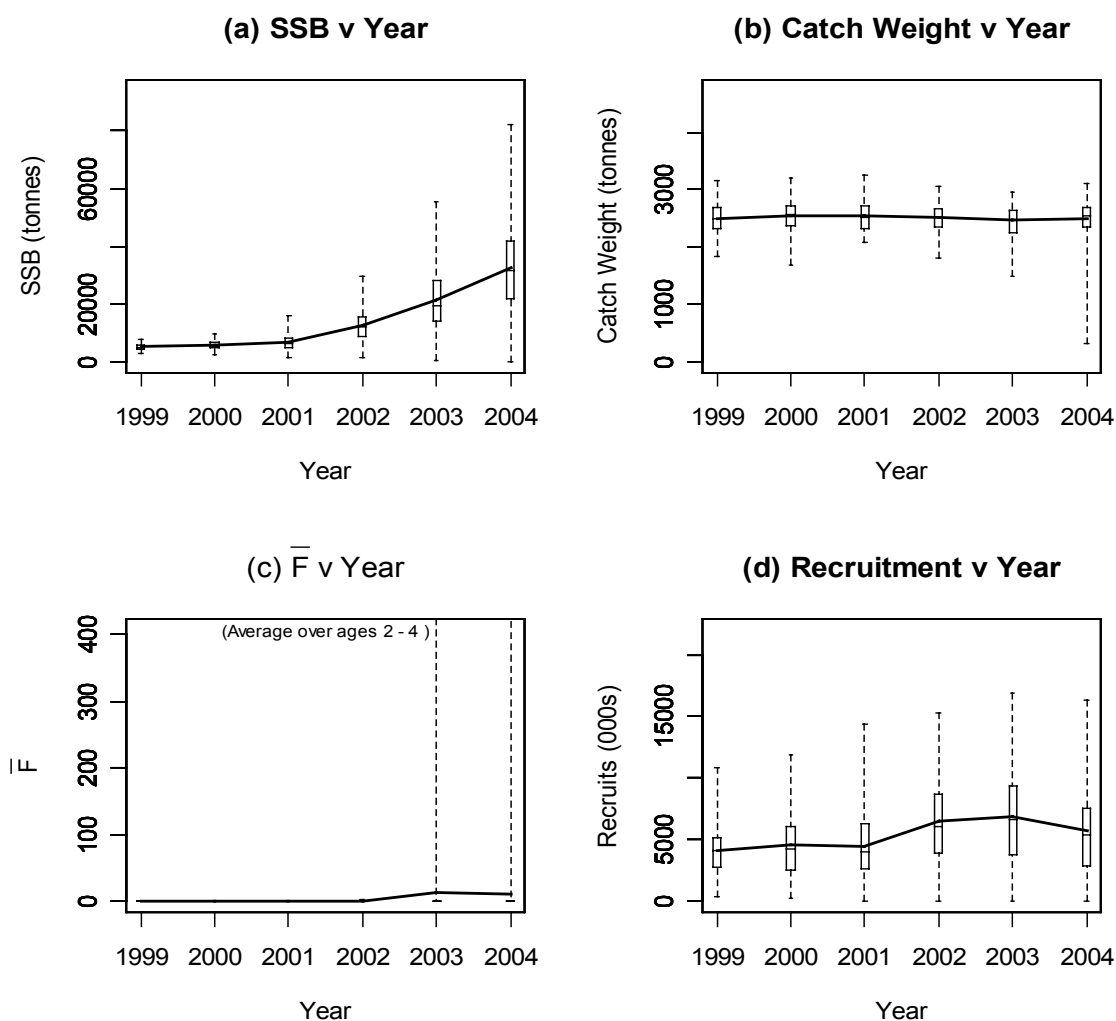


Figure 5. Time series plots of SSB, catch,  $\bar{F}$ , and recruitment, for projection of Irish Sea cod completed from 1999 – 2004. Projection uses TAC = 2500 tonnes for each year of the projection, with no implementation bias and a CV on TAC of 0.1. Recruitment is modelled using a stochastic Ricker function based on historical data. Note the high average  $\bar{F}$  values over all iterations indicating that at least some of the iterations resulted in a stock size falling to zero (note lowest SSB value in box and whisker plots). Note also that the largest SSB values are higher than that observed in historical data (so results may not be realistic when SSB is this large).

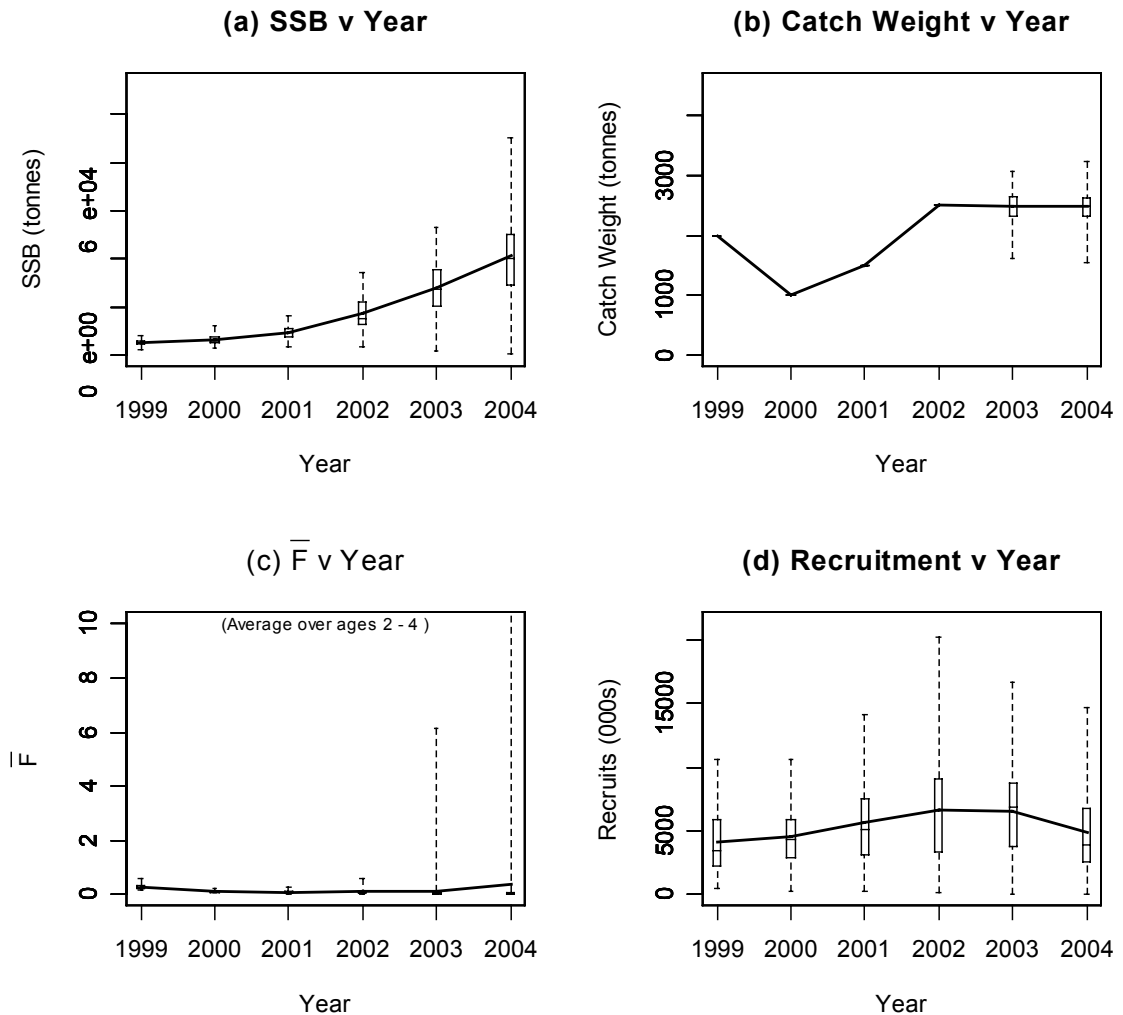


Figure 6. Time series plots of SSB, catch,  $\bar{F}$ , and recruitment, for projection of Irish Sea cod completed from 1999 – 2004. Projection uses fictional historical catches for 1999 – 2002, and then TAC = 2500 tonnes for 2003 – 2004. Note that there is no stochasticity in the historical catch values (this can be included if required). In 2003 – 2004 there is no implementation bias and a CV on TAC of 0.1. Recruitment is modelled using a stochastic Ricker function based on historical data. Note the high average  $\bar{F}$  values over all iterations indicating that at least some of the iterations resulted in a stock size falling to zero (note lowest SSB value in box and whisker plots). Note also that the largest SSB values are higher than that observed in historical data (so results may not be realistic when SSB is this large).

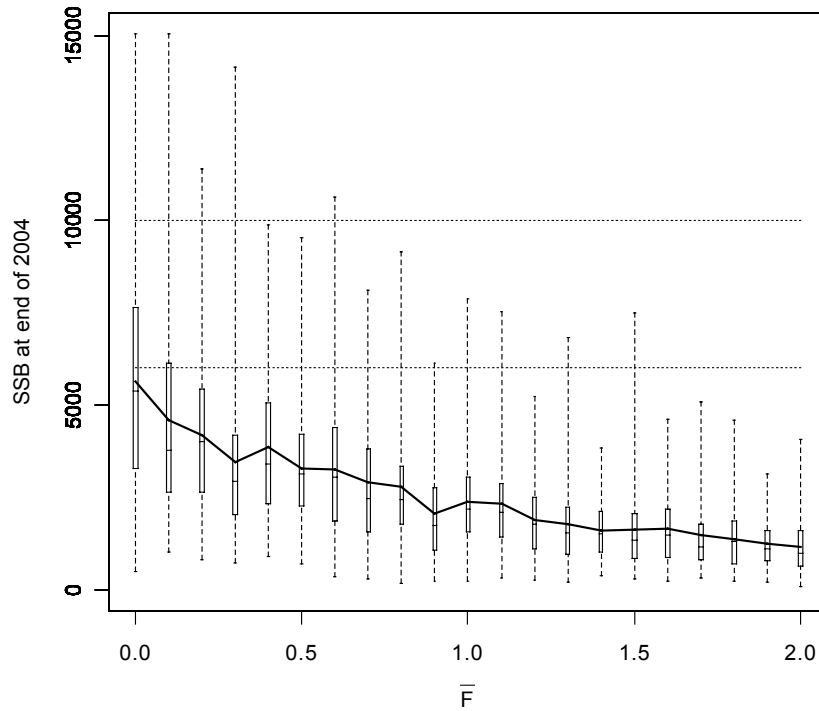


Figure 7. Plot of SSB at the end of the projection (2004) against a range of  $F$  values that are used in the final two years of the projection. There is a clear general trend – as  $F$  decreases, the expected final SSB increases (as may be expected). However, there is still a high degree of variability that should be considered.

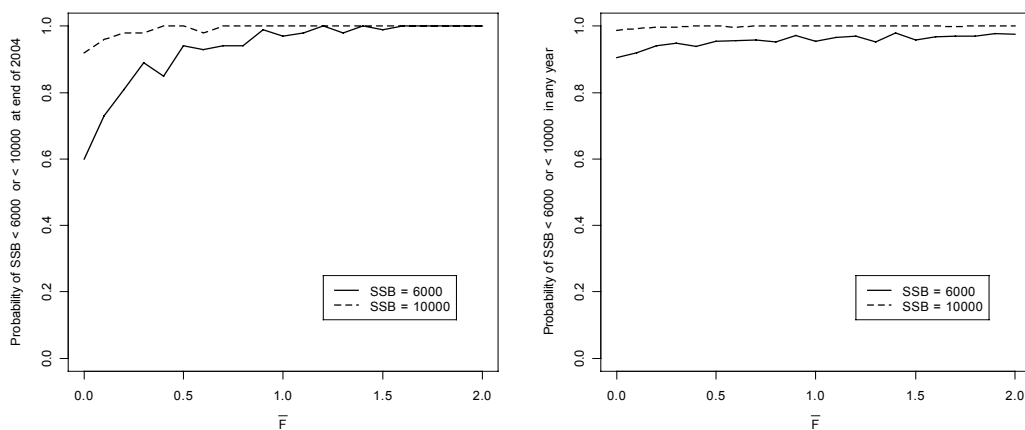


Figure 8. Plots showing the probability of SSB falling below  $B_{lim} = 6000$  tonnes and  $B_{pa} = 10,000$  tonnes in a) end of 2004; b) in any year against  $F$ . It is clear  $F$  needs to be low for a reasonable probability of being above  $B_{lim}$  at the end of 2004.

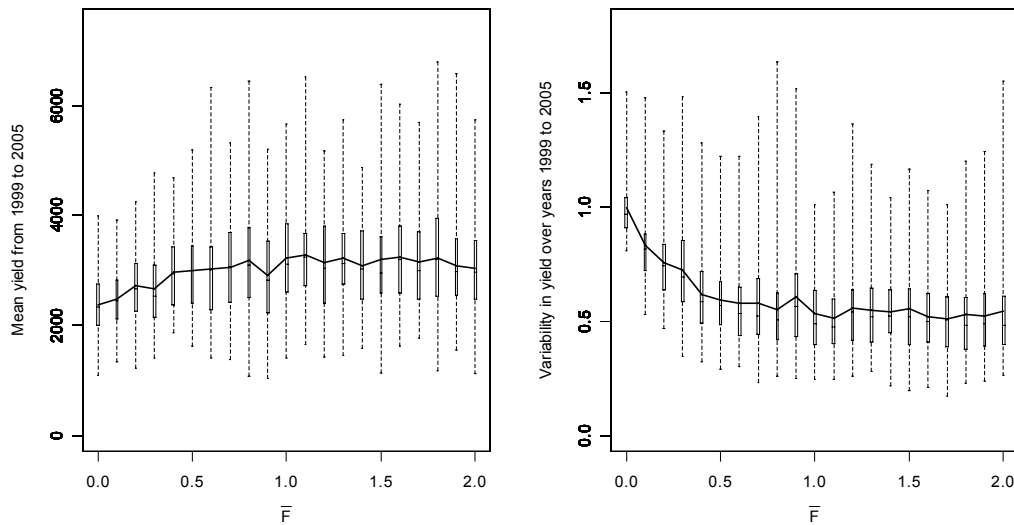


Figure 9. Plots showing mean yield and variability in yield over the projection period (1999 – 2004) against  $F$ . It should be noted that the highest expected yield is not achieved simply by fishing at the largest value of  $F$ . The high variability in yield for low  $F$  is because in 1999 – 2002 the projection uses  $F = 1.5$ .

## 4.2 Evaluating management strategies

When designing any long-term management plan, both the inherent variability of the fishery environment and also the uncertainty present in data collection and assessment estimates of the stock need to be considered. For example, any HCR that requires a very exact measure of the current SSB level will be unworkable as we are unlikely to ever know this. As F-PRESS attempts to model the qualitative uncertainty in the fishery system it is ideal for testing the robustness of different management strategies.

As discussed in Section 3.3, F-PRESS includes several simple generic HCRs based on either  $F$  or SSB as the decision rule variables. Other HCRs can be added and evaluated by the end user who has basic programming skills.

In the following plots we illustrate how F-PRESS could be used to evaluate a particular HCR. As in the previous section, we use Irish Sea cod data from 1999 as the input and recruitment data. Each projection is completed from 1999 – 2009 (10 year strategy), where the first three years use a fixed TAC of 2000 tonnes and then the remaining years of the projection use a new fixed TAC with  $CV = 0.1$ . The projections are completed over a range of values for these final fixed TACs – from 2000 to 10,000 tonnes.

We look at three different management strategies:

**A:** no HCR, projection runs just as in the previous section (Control);

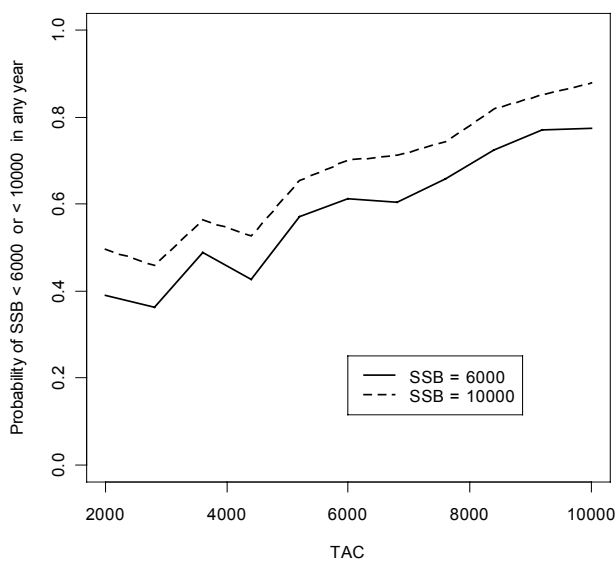
**B:** HCR decision rule is made every second year of the projection: if SSB is below  $B_{lim}$  ( $= 6000$  tonnes) then TAC = 0 for next 2 years; otherwise continue

with fixed TAC. Simulation assumes perfect observation / assessment (i.e. assessment bias = 1, assessment CV = 0).

**C:** HCR as given in B, but assume a 40% systematic overestimate in the assessment process (assessment bias = 1.4), with a random error of 10% (CV = 0.1).

Note that we are in no way suggesting these HCR models are sensible options for managing the Irish Sea cod stock! They are merely used to illustrate how a HCR may be evaluated using F-PRESS.

Now suppose that the most important consideration for managers is the risk to the stock. Figures 10 – 12 show plots of the probability of falling below  $B_{lim}$  or  $B_{pa}$  for the range of fixed TACs that are considered as part of the HCR. Note that for a full evaluation of a HCR the user would also need to consider other performance statistics such as the final year SSB and the mean and variability in yield, as shown in Section 4.1.2. Similar comparative plots could also be produced for a range of F values if required (if the fishery is based on F).



**Figure 10. Plots showing the probability of SSB falling below  $B_{lim} = 6000$  tonnes and  $B_{pa} = 10,000$  tonnes in any year against the fixed TAC value used for projections using no HCR. Note that with the higher TAC values there is a much greater probability of falling below  $B_{lim}$ .**

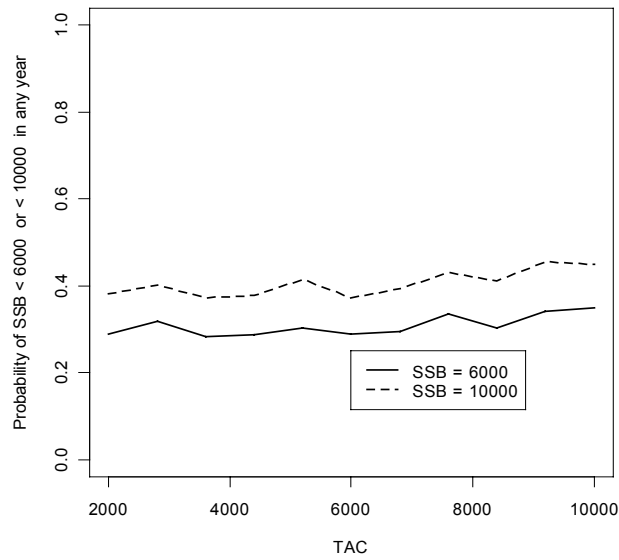


Figure 11. Plots showing the probability of SSB falling below  $B_{lim} = 6000$  tonnes and  $B_{pa} = 10,000$  tonnes in any year against the fixed TAC value used for projections using HCR B and no assessment error or bias. Note that there is a reasonably low probability of falling below  $B_{lim}$  for all the TAC values used.

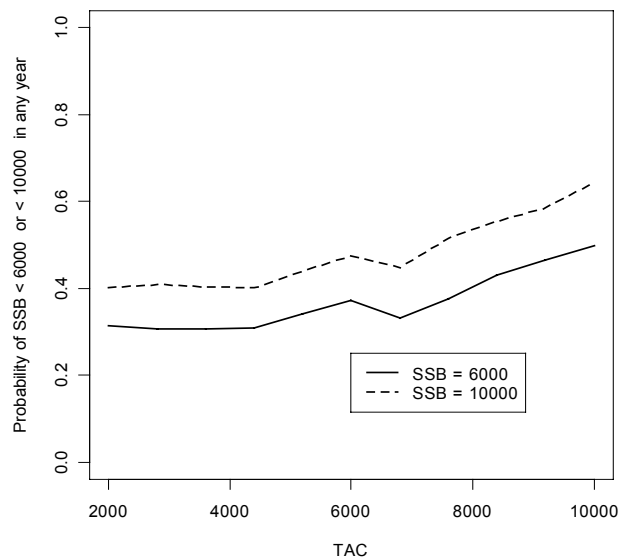


Figure 12. Plots showing the probability of SSB falling below  $B_{lim} = 6000$  tonnes and  $B_{pa} = 10,000$  tonnes in any year against the fixed TAC value used for projections using HCR B and assessment bias of 40% and error of 10%. Note that with the higher TAC values there is a higher probability of falling below  $B_{lim}$ . Comparing to Figure 11, it is clear that at higher TAC values, the effect of assessment/observation error is significant.

Thus, by comparing the performance statistics of different management strategies or HCRs it is possible to make judgements about the relative robustness or suitability. With option C above (assessment error and bias), we are able to control and quantify the level of error in the assessment process and see how this directly affects the performance of the HCR (compare Figures 11 and 12). This is an advantage of our simple model – if we used a complex assessment feedback model it would be much more difficult to control and quantify the levels of error introduced.

## **5 Discussion and Conclusions**

F-PRESS is a new simulation tool based on a simple stochastic operating model that can be used to develop probabilistic assessment advice or to evaluate management strategies or HCRs. F-PRESS has been designed to fit into the conceptual framework for simulations as described by ICES (2004a; 2005). With the new 'long-term' management approach that is being promoted by ICES (SGLTA; ICES, 2004c), there is a real need for flexible software that is freely available to use now, so that HCRs can be developed, tested and evaluated. F-PRESS is available now and can easily be recoded by the end user to test any appropriate management plan or HCR. Although there are some limitations with our deliberately simple approach, simulation results will still provide a useful insight into the likely status of fish stocks under different management strategies. The open-source approach using R allows the simulation algorithm and code to be easily understood, edited and adapted by the end user. Ongoing validation is required, especially if users adapt the code themselves, but this is easily facilitated by the open-source nature of the code.

We have not attempted to directly compare and contrast the approach taken in F-PRESS to existing software used by the ICES community (descriptive comparisons are available in ICES, 2005). Further comparative studies will be undertaken to compare F-PRESS results with results from more complex simulation models that may be used to evaluate management strategies. F-PRESS has been designed to complement existing software and offer an alternative approach and results should only be considered in this context.

It should be noted that the functionality discussed and illustrated in this paper refers to the latest version of the software at time of press – currently F-PRESS Version 1.0. Due to the open source nature of the code and anticipated further development, future versions of the software may have different functionality or operate in a different manner. However, the methodology and underlying approach of a deliberately simple qualitative model used for indicative purposes will remain.

The F-PRESS source code files, 'F-PRESS User Manual', and 'F-PRESS Technical Manual' are all freely available from the authors. As the development of the F-PRESS software is an ongoing project, we would appreciate any suggestions for further program design or refinement, along with any validation or error reports.

## **Acknowledgements**

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## **Appendix I - Summary of F-PRESS key points**

### Program code:

- programmed to run in R 2.0;
- open source and freely available code;
- run using an 'Options' file;

### Operating model:

- single species;
- age structured;
- non-spatial;
- exponential mortality (M – natural, F – fishing, and  $F_d$  discards);
- stochasticity added to original fishery and stock parameters each year using a Normal distribution for the noise;
- various stochastic recruitment models;
- fishery based on F or TAC (using an F multiplier on F at age vector);
- implementation errors modelled implicitly in F or TAC;

### Observation / Assessment model:

- bias and random noise applied to F and SSB parameters (used in HCRs);
- user can quantify and understand how error/bias affects robustness of HCRs;

### Management model:

- simple generic HCRs based on variables F and SSB along with other specified (fixed) parameter values;
- more complex HCRs require end user to edit / adapt the source code;

### Data Inputs:

- File 1: stock and fishery parameter data with CV values;
- File 2: 'historical' recruitment data (if required);
- File 3: 'historical' catch file (if required);

### Using the tool:

- Simulation option 1: A projection is completed for a number of years with a fixed F or TAC each year;
- Simulation option 2: A range of F or TAC values are specified by the user and the simulation completes a whole iterative run of projections for each value of F or TAC;

Data outputs:

- all yearly data for each iteration in projection saved in file;
- data overwritten every projection if simulation option 2 used;
- performance statistics can be calculated to compare HCRs;

Graphical outputs:

- time series plots of SSB, catch, F, and recruitment;
- plot of F or TAC against stock size in final year of projection;
- plot of F or TAC against probability of being below (or above) stock reference points (e.g. Blim or Bpa) during projection;
- plot of F or TAC against mean yield over projection and variability in yield over projection;
- other graphics options available or can be added;

Limitations of simulation tool:

- CV data may not be available – arbitrary choice;
- recruitment functions may only be valid over historical SSB range;
- 'shifting baseline' not currently modelled;
- temporal correlations not modelled;
- software is slower than programs using compiled code (C, Fortran etc);
- program and code need further testing and validation;
- end user adaptations/editing may introduce errors.